What prompts the adoption of car restriction policies among Chinese cities

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Abstract

Facing rapid motorization, many Chinese municipalities are implementing policies that restrict car ownership or use. However, there is significant variation in terms of which cities adopt these policies and when. This research systematically investigates what factors prompt local governments in China to adopt these car restriction policies. We collect a database of car restriction policies as well as economic, demographic, land use, and transportation indicators for 287 Chinese municipalities from 2001 to 2014. We adopt a mixed methods approach that combines a qualitative investigation of stated objectives and legislative precedent within policy documents with a quantitative duration model of policy adoption. We find that the adoption of comprehensive car ownership and use restriction policies across Chinese cities primarily responds to local air pollution and secondarily to car ownership and congestion. Policy adoption additionally responds to local subway line constructions. Local economic power and population size do not effectively explain policy adoption. Idiosyncratic effects at provincial or city levels are important, although the underlying mechanisms by which these network effects manifest remain unclear. Broadly, our findings suggest that problem solving and network effects both contribute to the adoption of car restriction policies across China's cities and that the legal policy documents reliably illustrate the motivations of these policies.

Keywords: car restriction policies; Chinese municipalities; policy adoption; duration model; text analysis

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1. Introduction

Chinese cities have been subject to accelerated urbanization and motorization over the past two decades, leading to issues such as congestion, local air pollution, and energy shortages (Yang, et al., 2014). To combat these issues, Chinese cities are adopting new urban transportation management strategies (Li, 2017). China is often seen as a top-down, command and control system with policymaking power vested in the national government; however, when it comes to transportation policy, city governments have enjoyed significant autonomy and discretion in addressing local challenges of traffic congestion and local air pollution (Wan, Wang, & Sperling, 2013). In particular, major cities have increasingly implemented policies that restrict both car ownership and car use (Xuan, et al., 2013).

In this study, we consider the adoption of comprehensive car restriction policies. By "comprehensive" we mean those policies that are citywide, that are in effect year-round, and that encompass most types of vehicles. These comprehensive car restriction policies include car use restrictions (often based on the last digit of the car license plate[1]) and car ownership restrictions (rationing the number of new license plates sold in a city and allocating these licenses through lottery or auction). We do not consider policies that limit car use in specific areas, during specific time periods, or for specific types of vehicles.[2]

While more Chinese cities are adopting car restriction policies each year, there is significant heterogeneity in terms of which cities adopt which types of policies when. This paper explores what causes cities to decide whether or not to adopt comprehensive car ownership or use restrictions, and what characteristics of the municipalities help determine the timing of their adoption.

Based on existing literature on municipal policymaking, we hypothesize that the adoption of car restriction policies could be driven by some combination of:

1. *Problem solving:* Policies are adopted to solve local problems (e.g., Chun, Moody, & Zhao, 2019; Turnbull, 2006). In the case of car restriction policies, these problems may be air pollution, congestion, or other negative externalities caused by automobile ownership and use (Yang, et al., 2014).
2. *Power:* Municipalities with more political, economic, or financial power are more likely to adopt a policy (Shi, Chu, & Debats, 2015).

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[1] For instance, a car with an odd digit as the ending number of the license plate cannot drive on certain days, and similar rules could be applied to a car with an even digit as the ending number.

[2] This study excludes more selective and intermittent car use restrictions such as policies that limit driving in only some geographical regions of the city, during certain times of day (such as rush hour), on particular days (such as days of high-pollution or during special events), or for certain car types (such as those causing serious pollution problems).

3. *Local conditions:* The adoption of policies might respond to local conditions not directly related to local problems (e.g., Trappel, 2016). In the case of car restriction policies, these may include transportation service and infrastructure conditions (such as local subway lines, buses, or taxis) or local land use patterns (such as urban density).
4. *Network effects:* Municipalities adopt policies due to regulations or other pressures from central government to local government, a regional effect from one municipality to another because of geographical closeness, or a policy learning process across municipalities (e.g., Timms, 2011; Marsden & Stead, 2011; Marsden, et al., 2011).[3]
5. *Other factors:* Local officials may adopt policies for reasons other than the above factors, including considerations of political economy and ideology (e.g., Glaeser & Ponzetto, 2018; Ichimura, 1998).

However, it is difficult to know a priori which of these different drivers contribute most to the adoption of certain policies. In this study, we analyse which factors prompt 287 Chinese municipalities to adopt comprehensive car ownership and use restriction policies during the period from 2001 to 2014. Using a mixed-methods approach that combines examination of the text of policy documents and quantitative duration models, we explore which of the hypotheses above apply in the context of car restriction policy adoption. We directly investigate hypotheses 1–3 using different explanatory variables in our duration models and indirectly investigate hypothesis 4 by incorporating heterogeneous city and region effects. Having investigated hypotheses 1–4, if significant unexplained variation in the adoption patterns of car ownership and use restrictions still remains across Chinese cities, this might suggest that other factors (hypothesis 5) are significant contributors.

1.1. Our Contribution

While the policy adoption process among China's cities is complicated by significant variation in local contexts and by the five competing hypotheses discussed above, this study corroborates that problem solving—in response to air pollution and car consumption—is the dominating motivation for adoption of car restriction policies. While the findings may seem intuitive, this study is able to quantify the magnitude of these motivations through rigorous application of quantitative and qualitative methods, using a data set with large geographical and temporal span (287 cities and 14 years) covering a comprehensive list of historical economic and transportation variables, and applying econometrics models built in a systematic manner. In addition to contributions to the discussion of transportation policymaking in Chinese cities, we make methodological contributions by using duration models to analyse the adoption of local transportation policies. Our focus on policy adoption as the outcome rather than as an

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[3] For example, one leader city (such as Beijing or Shanghai) may adopt a policy, after which other cities follow suit (Li, 2007).

input is different from and complementary to past studies that mainly describe and evaluate the impacts of car restriction policies in China by treating policy adoption as an exogenous factor. Our work informs this predictive and evaluative work by taking policymaking as an endogenous factor responding to local conditions.

In the following sections, we review pertinent literature relating to both the context of transportation policymaking in China's cities and the study of policy adoption; introduce our data and methods; and present the results of our qualitative investigation of policy documents followed by the results from the duration models and the tests of their robustness. We then discuss our findings and their implications for understanding transportation policymaking (in Chinese municipalities and in broader contexts) and a research agenda for examining policy decision as an endogenous factor in the transportation field.

2. Literature Review

The transportation policymaking landscape at the city-level in China is extremely complex. Across China's 287 cities, there are significant differences in land use and transportation conditions that map to differences in the types of transportation policies that are adopted (Moody, et al., 2019). Yet the bi-directional interactions among local conditions and transportation policies among Chinese cities is still an under researched area. While significant literature has taken an evaluative approach to explore how transportation policies (particularly car ownership and use restrictions) impact local conditions in Chinese cities, fewer studies have looked at how local conditions and other factors may prompt the adoption of certain transportation policies across a diverse set of cities. In this study, we address this research gap by applying policy adoption models from other fields of study to the case of car restriction policy adoption at the city-level in China.

2.1. Impacts of Policy Adoption on Local Context: China's Car Restrictions

Prior studies of China's municipal transportation and environmental policies have often been conducted on a city-by-city basis, focusing on the effect of these policies on the local context rather than considering the reverse direction (i.e., how local or regional conditions could prompt the adoption of policies). This is particularly true when considering existing literature on car ownership and use restrictions in China's cities.

Restrictions on car ownership (by lottery, auction, or hybrid mechanisms) have been studied in terms of their impacts on: aggregate car ownership growth (Yang, et al., 2014; Zhang, 2014), individual vehicle purchase decisions (Xiao, Zhou, & Hu, 2013); gasoline consumption and pollutant emissions (Yang, et al., 2014; Xiao & Zhou, 2014); sales of electric vehicles (Ma, Fan, & Feng, 2017); use of vehicles (Chang, Duan, & Yang, 2018); and social welfare (Li, 2017; Wang & Zhao, 2017; Zhu, et al., 2013; Ye & Yin, 2013). Different types of car use restrictions have also been studied in terms of their impacts on congestion and driving behaviour as well as air quality and pollution

(Liu, et al., 2016; Yang, Lu, & Qin, 2016; Sun, Zheng, & Wang, 2014; Cao, Wang, & Zhong, 2014; Zhao, Xu, & Wang, 2010).

However, policy decisions and local conditions have a bi-directional relationship. Cities with car restriction policies might more effectively mitigate air pollution, but at the same time cities with more air pollution might be more likely to adopt car restriction policies. Policy evaluation literature often exclusively focuses on the former causal relationship, while neglecting the fact that policy decisions can be determined by many local conditions. This can lead to an endogeneity problem, which may generate misleading predictions about future fleet size, congestion, or air quality. Thus, in this study we analyse the determinants of adopting car restriction policies, which reverses the common direction of policy evaluation analysis.

2.2. Impacts of Local Context on Policy Adoption

This reverse question of what factors prompt governments to adopt certain policies is often analysed using duration models. Variations of these models have been applied to look at policy adoption in many different domains and at multiple levels of government. Across countries, duration models have been applied to model the adoption of air emission standards (Biesenbender & Tosun, 2014) and renewable energy policies (Stadelmann & Castro, 2014; Jenner, et al., 2012). At the state-level, studies have looked at adoption of environmental audit initiatives (Stafford 2006), commercial building energy codes (Nelson, 2012), renewable portfolio standards and other green electricity policies (Lee, Kim, & Lee, 2016; Lyon & Yin, 2010). Among cities and municipalities, duration models have been used to look at restrictions on the pornography industry (Jones & Branton, 2005), local option sales taxes (Sjoquist, et al., 2007), and city-level contracts for water management (González-Gómez & Guardiola 2009).

As the studies above demonstrate, the use of duration models to explore how local and regional conditions prompt the adoption of public policies is well established across multiple disciplines. Yet there are no such examples of duration models applied to policy analysis in the transportation domain, despite the widespread use of these models for other research questions.[4] In this study, we demonstrate the value of applying

[4] While duration models have not been applied previously to look at the adoption of transportation policies, they have been applied widely for other applications within the transportation domain. For examples, researchers have traditionally used duration models to analyse activity and travel patterns (Juan & Xianyu, 2010; Joly 2006; Bhat, 1996; Mannering, et al., 1994) and vehicle ownership (De Jong, 1996; Gilbert, 1992). More recently, duration models have also been applied to better understand accident data, including modelling of traffic incident duration (Tavassoli Hojati, et al., 2013), crossing behaviour of cyclists at intersections (Yang, et al., 2015), driver braking times (Fu, et al., 2016; Bella & Silvestri, 2016), vehicle distance travelled in run-off-road crashes (Roque & Jalayer 2018), and minimum gap time for lane changing (Ali, et al 2019). Other applications

duration models to understand the policy adoption process for municipal car ownership and use restrictions among Chinese cities.

3. Methodology

To identify the factors that prompt the adoption of car ownership, we adopt a mixed methods approach that combines a qualitative investigation of stated objectives and legislative precedent within policy documents with a quantitative duration model of policy adoption.

3.1. Data

First, we compiled a database of comprehensive car ownership and use restriction policies by year for 287 Chinese cities from 2001-2014. An initial key word search was conducted using the database of Peking University Law Compilation (PULC). The PULC search was complemented by a city-by-city key word search on Google and Baidu. This second search filled most of the missing information of our dataset collected from PULC, although we still cannot guarantee its completeness. In the end, we obtained 116 relevant legal documents, each of which provides details of a car restriction policy adopted by one city in one specific year. These documents cover car ownership and use restriction policies adopted in 46 unique cities in China between 2001 and 2014 (see Map 1).

For the qualitative analysis, we extracted information from the policy documents such as which national and/or local laws and regulations they cite to support the legitimacy of the restriction as well as the local government's stated objectives in implementing the policy. For the quantitative adoption models, a binary indicator of whether or not a policy had been adopted in any given city-year pair was taken as the dependent variable.

For the quantitative model, independent variables were compiled for the same 287 Chinese cities from 2001-2014. Standardized and comparable indicators of economic, transportation, and urban development were compiled from the China Premium Database from CEIC. We refined and cross-validated the information in the CEIC database by manually comparing outlier values and missing data points by city and year to the annual China City Yearbooks and numerous municipal and provincial yearbooks. Subway length was integrated into our database from the website of the China Association of Metros. Finally, air pollution index (API) values were collected for the cities from the official website of China's Ministry of Ecology and Environment. Both mean and maximum API values in a given year were recorded for each city.

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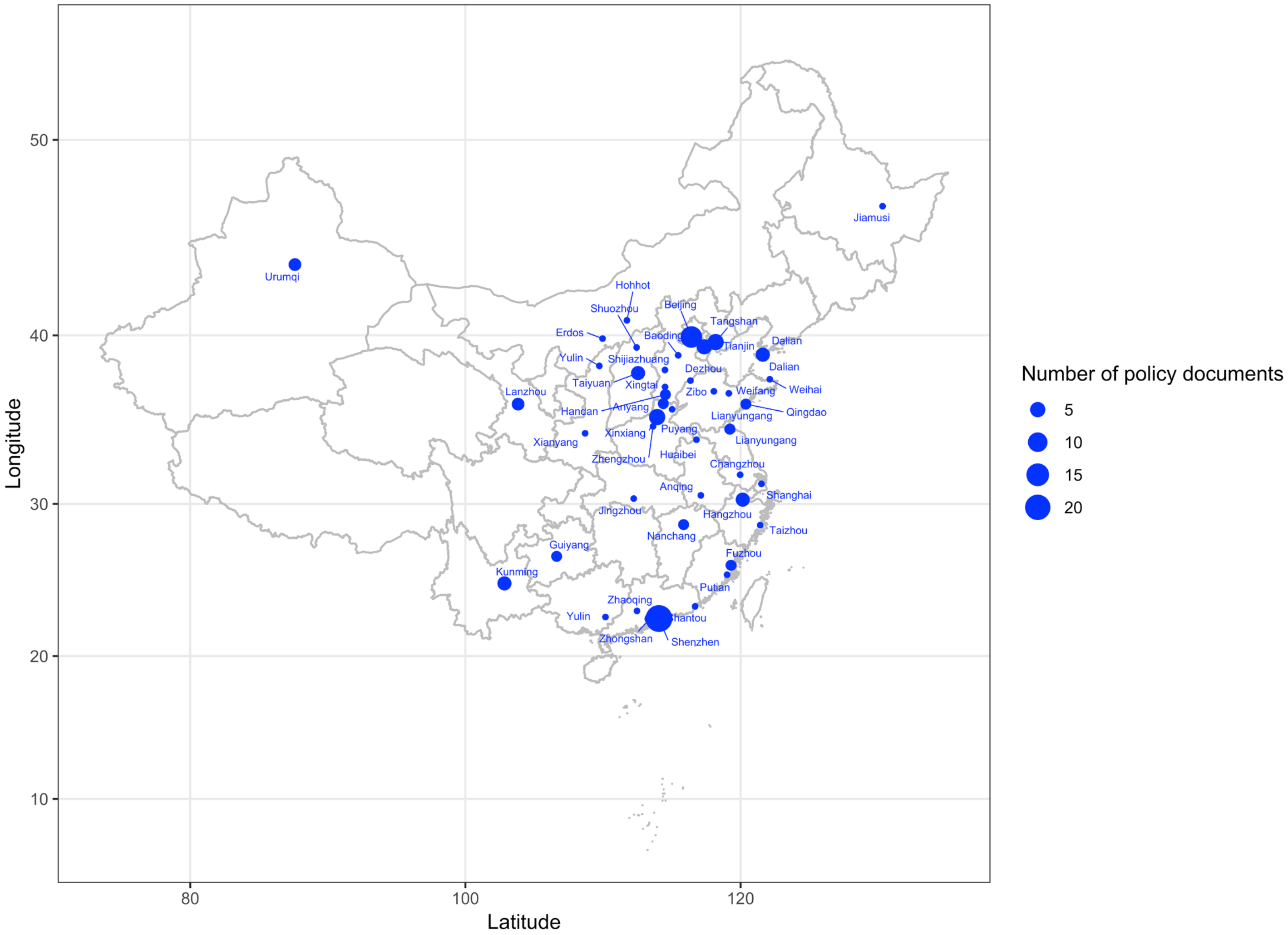
of duration models in the transportation field include the analysis of transit user loyalty (Nishiuchi & Chikaraishi, 2018; Trépanier, Habib, & Morency, 2012) and modelling the acquisition of drivers licenses (Habib, 2018).



Map 1. Spatial distribution of the car ownership and use restriction policy documents reviewed.

Most variables have close to complete data but the air pollution data is not complete: about two-thirds of the cities were missing. Hence we adopted two methods to address the missing data problems (Gelman & Hill, 2006). For the variables other than air pollution, we used common imputation methods to fill in the data. Imputation is acceptable in this case because the observed variables provided enough information for the approximation of missing variables. For API, the large amount of missing information rendered data imputation inappropriate. Therefore, we create a new binary variable to indicate whether a data point is observed (0) or missing (1). Then both observed air pollution data and this missingness indicator are used in modelling as explanatory variables.

2.2. Duration Models

We choose to use a duration model because it makes better use of our longitudinal data than a binary logistic regression (often used to understand variation in discrete variables). For our data, duration models are a better choice than logistic regression because duration models capture the dynamics of the discrete variables by conditioning on the past decisions y_{t-1}, while logistic regressions focus on only the static associative relationships without conditioning on the past (Jones & Branton, 2005; Bhat, 1996; Gilbert, 1992). Duration models require a panel dataset covering a long time span, while logistic regressions need only a cross-sectional dataset. Duration models have been shown to perform better than logistic regressions in modelling binary outcomes over time because they capture the dynamics of discrete variables, while logistic regressions focus only on static associative relationships.

Among the duration models available in the literature, we employ a Cox duration model using as the dependent variable a binary indicator of whether or not a comprehensive car ownership or use restriction is adopted for each city-year pair.[5] The Cox model is a semi-parametric model that uses the proportionality hazard assumption (shown to be more flexible than the Weibull model using a parametric hazard function) (Cox, 1972). As a robustness test of our baseline duration models, we incorporate random effects to capture the unobserved heterogeneity of provinces and municipalities (Han & Hausman, 1990). The unobserved heterogeneity can be approximated by parametric probabilistic distributions, such as gamma or normal distributions, or addressed by a non-parametric method (Hausman & Woutersen, 2014; Han & Hausman, 1990; Lancaster, 1979).

One key assumption in the duration model is the proportional hazard function that describes $P(y_t = 1 \mid y_{t-1} = 0\,)$, the conditional probability that one municipality started to implement the car restriction policy at year t:

$$P(y_t = 1 \mid y_{t-1} = 0\,) = \lambda(t) = \lambda_0(t) * \mathrm{e}^{-x_{it}\beta + \delta_i + \epsilon_{it}} \quad (1)$$

[5] For the few cities, like Beijing, that have adopted both a comprehensive car use restriction and a car ownership restriction, only the first policy adopted is modeled.

where i indicates city; t is time; x_{it} is any time-variant covariate (such as the number of automobiles per capita, GDP per capita, or total urban population for city i in year t); λ_0 is the baseline hazard function; δ_i is the unobserved heterogeneity of each individual city or province; and ϵ_{it} is the unobserved error term across city-time pairs assumed to have independent and identical distributions.

Explanatory Variables

To explain policy adoption, we considered sets of explanatory variables that match to our hypotheses: 1) problems connected to car ownership and use, 2) municipal power, 3) local transportation and land use conditions, and 4) network effects. Table 1 provides summary statistics for the start (2001) and end (2014) of the study period. Where appropriate, we divided indicators by total urban population (or urban area) to control for differences in the size of China's 287 cities.

First, we include local problems related to car ownership and use in China (Yang, et al., 2017; Wu, Zhao, & Zhang, 2016). This study focuses on air pollution, car ownership, and congestion. For air pollution we use both the mean and maximum air pollution index (API) for each city in a given year. We also control for total industrial emissions per capita for each city. For car ownership, we use a measure of motor vehicles per capita. For congestion, we are limited to proxy indicators based on data comparability and availability. Unable to find comprehensive data on average travel times or speeds in each of China's 287 cities during the 14-year period, we use vehicle density (1000 vehicles / road area) as our measure of congestion.

Second, the power of municipalities can be measured by financial capacity, stability of local government, average income level, and institutional capacities (Shi, Chu, & Debats, 2015; González-Gómez & Guardiola, 2009; Sjoquist et al., 2007). For this study, we use GDP and total urban population as indicators of economic and political power, because higher GDP and larger city sizes are typically associated with higher political tier and more political capital.

We approximate local transportation and land use conditions using the numbers of subway lines, buses, taxis, urban density, and road area (Maat, van Wee, & Stead, 2005; Cervero & Landis, 1997).

Finally, we also explore potential network effects, approximated by including dummy variables for both the provincial and city levels.

Table 1. Summary statistics of the independent variables

	2001					2014				
	Mean	Std Dev	Min	Median	Max	Mean	Std Dev	Min	Median	Max
Motor vehicles per capita	0.02	0.02	0	0.01	0.25	0.11	0.1	0.01	0.08	0.94
Mean API	12.13	31.1	0	0	160.52	84.57	45.46	0	91.23	226
Max API	39.07	110.07	0	0	500	202.94	158.64	0	163	500
API dummy (0/1)	0.85	0.36	0	1	1	0.16	0.37	0	0	1
Industrial emission per capita (million tons)	0.02	0.03	0	0.01	0.28	0.02	0.03	0	0.01	0.27
Total urban population (million)	1.24	1.69	0.16	0.77	15.87	1.65	2.57	0.16	0.92	23.11
Real GDP per capita (1000 RMB/person)	16.58	22.48	2.77	11.53	317.62	54.91	51.21	9.27	40.38	481.68
Taxi per 1000 people	0.78	1.04	0.02	0.4	7.79	0.83	0.94	0.04	0.42	5.15
Bus per 1000 people	0.19	0.3	0	0.08	2.65	0.33	0.43	0.02	0.18	4.54
Subway length (m) per 1000 people	0.05	0.46	0	0	5.4	0.92	3.99	0	0	36.47
Subway dummy (0/1)	0.02	0.13	0	0	1	0.07	0.26	0	0	1
Road area per capita (m^2/person)	2.12	4.22	0.05	1.08	54.06	5.04	6.65	0.23	3.21	72.87
Urban density (person/1000 m^2)	21.9	15.26	3.16	17.68	156.21	12.57	7.23	2.68	11.08	74.5

Many other variables could affect policy adoption, such as the relationship between municipalities and central governments, leadership, or public awareness of problems (Shi, Chu, & Debats, 2015; Stafford, 2006). These other factors (related to hypothesis 5) are not explicitly incorporated in this study. These missing variables may be captured in the random error terms and time dummies in the duration model as long as the variables are time-invariant or entity-invariant. However, some missing variables that are time-variant, such as the idiosyncrasies of local leaders in a particular governmental administration, could engender some statistical problems for our model.

4. Qualitative Results from Policy Documents

To answer the question of what prompts local municipalities to adopt car restriction policies, we examine the qualitative features extracted from the 116 policy documents in our database. These policy documents typically enumerated the objectives of the policy as well as any national laws and local regulations cited to support its legitimacy. Calculating the percent of policy documents that cite certain objectives or legislative precedents (across all cities and years), provides insight into what municipal government officials claim to be the drivers of car restriction policies (Table 2).

Considering the stated policy objectives, the most important motivation of adopting car restriction policies was the improvement of air quality and a secondary motivation was to mitigate congestion. We find that about 84% of the car restriction policies referred to improving air quality or addressing pollution as their objective, with an additional 28% adopting the policy for the related objective of improving public health. Additionally, 21% of the policy documents referred to mitigating transportation congestion (18.1%) or improving travel efficiency (2.6%) as the policy purpose. Considering legislative precedent, we find that 44% of all car restriction policies cited national laws related to transportation and road safety and that 30% cited national laws related to air pollution prevention. Among local laws, local pollution mitigation regulation was the most often cited (with 51%).

Table 2. Percent of car restriction policy documents citing each objective or legislative precedent

Policy Objectives Cited	%	Laws Cited	%
Improve air quality or address pollution	83.6	National: transportation and road safety	44.0
Improve public health	28.4	National: air pollution prevention	30.2
Mitigate transportation congestion	18.1	National: environmental permit of auto regulation	2.6
Ensure road safety	6.0	Local: pollution mitigation regulation	50.9
Ensure construction safety	2.6	Local: road & transportation regulation	12.1
Increase travel efficiency	2.6	Local: regulation on environmentally non-friendly cars	6.9
Improve transportation circumstances	0.9	Local: emergency act on pollution days	6.0

Thus we find that local governments claim to adopt car restriction policies to improve air quality and, secondarily, to mitigate congestion. Next, using quantitative models we empirically test whether city-level adoption of comprehensive car restriction policies does indeed respond to local air pollution and the number of vehicles on the road.

5. Quantitative Results from Duration Models

In this section, we present the quantitative results from the duration models. First we present the baseline model used to assess the statistical significance and predictive accuracy of 14 indicators measuring economic growth, population, air pollution, urban density, and local transportation conditions in predicting the adoption of car restriction policies. Next we translate these findings into elasticities of policy adoption probability. Finally, we perform robustness test by incorporating provincial and city idiosyncratic effects.

5.1. Baseline Models

Table 3 shows the results of four duration model specifications. Based on our qualitative review of policy documents, our models explain policy adoption using measures of motorization and air pollution. We additionally control for variables related to current transportation conditions, population and economic activity, and urban form. Model 1 uses car ownership (motor vehicles per capita) as its explanatory variable for motorization, while Model 2 additionally incorporates vehicle density (vehicles/road area) as a proxy for congestion. Model 3 is specified as Model 1 but additionally includes the interactions between the API missing dummy and all other variables in the model. Model 4 is specified as Model 1, but calculated only for the 1,200 city-year observations with complete variables. Thus, Models 3 and 4 test the robustness of the conclusion from Model 1 against potential missing data bias and sampling, respectively.

Model 1 shows that the adoption of car restriction policies is significantly associated with car ownership (+16.460), mean and maximum API values (+0.042 and +0.009), and local subway system existence (+3.107) and length (-0.333). We find that cities are more likely to adopt car restriction policies when they have more registered automobiles per capita and when they face greater local air pollution issues (larger values of both mean and maximum API). Cities with subway lines are more likely to adopt car restriction policies. This is probably because cities determined to develop sustainable mobility patterns might see subway system development and car restriction policies as complementary strategies. Conditioning on the existence of subway lines, the cities with longer subway lines are less likely to adopt car restriction policies. This could be because cities with longer subway systems have a more robust rapid transit alternative to automobile use and therefore feel lesser need to further restrict car ownership or use. The results in Model 1 suggest that the decision to adopt a car restriction policy in a given city in a given year responds to local problems, particularly car ownership and air pollution, rather than general demographic, economic, or urban conditions. The results also suggest that the adoption of car restriction policies is related to local subway systems rather than other modes of public transit such as buses or taxis.

Table 3. Duration model results: unstandardized coefficient (and standard error)

	Model 1	Model 2	Model 3	Model 4
Motor vehicles per capita	16.460**	20.575*	16.838*	17.130*
	(8.143)	(11.618)	(9.821)	(10.008)
Vehicle/road area		-0.024		
(1000 vehicles / million mi^2)		(.047)		
Mean API	0.042**	0.043***	0.041**	0.039**
(0-500)	(.016)	(.016)	(.018)	(.018)
Max API	0.009**	0.009**	0.008*	0.008*
(0-500)	(.004)	(.004)	(.004)	(.004)
API missing dummy (0/1)	4.845**	5.013**	6.903*	
	(2.15)	(2.191)	(3.683)	
Industrial emission	-6.285	-6.413	2.276	3.012
(million tons)	(15.491)	(15.365)	(13.686)	(13.938)
Total urban population	0.185	0.179	0.673*	0.643*
(million)	(.143)	(.145)	(.355)	(.352)
Real GDP per capita	-0.025	-0.025	-0.047	-0.047
(1000 RMB/person)	(.022)	(.022)	(.037)	(.037)
Taxi per 1000 people	-0.171	-0.193	-0.211	-0.197
	(.622)	(.643)	(.822)	(.82)
Bus per 1000 people	0.815	0.645	0.101	0.172
	(1.664)	(1.766)	(2.284)	(2.201)
Subway length (m) per 1000 people	-0.333**	-0.326**	-0.584***	-0.580***
	(.157)	(.159)	(.217)	(.219)
Subway dummy (0/1)	3.107***	3.039**	2.995**	2.913**
	(1.182)	(1.183)	(1.449)	(1.461)
Road area per capita	0.04	-0.015	0.116	0.106
(m^2/person)	(.099)	(.152)	(.142)	(.142)
Urban density	-0.08	-0.072	-0.127	-0.123
(person/1000 m^2)	(.088)	(.089)	(.118)	(.118)
Interaction between API missing dummy and all other variables	N	N	Y	N
Number of observations	3,916	3,916	3,916	1,200
R^2	0.012	0.012	0.015	0.031
Maximum possible R^2	0.031	0.031	0.031	0.071
Log likelihood	-37.497	-37.352	-32.599	-25.242
Wald test	36.300***	35.910***	35.340**	23.080**
	(df =13)	(df = 14)	(df = 22)	(df =12)
Likelihood ratio test	47.658***	47.949***	57.454***	38.012***
	(df =13)	(df = 14)	(df = 22)	(df =12)
Score (log-rank) test	115.762***	115.931***	144.064***	62.224***
	(df = 13)	(df = 14)	(df = 22)	(df =12)

Note: $p < 0.1$ *; $p < 0.05$ **; $p < 0.01$ ***

The comparison between Models 1 and 2 suggests that car restriction policies are mainly adopted in response to auto ownership per capita rather than vehicle density (as a proxy for congestion). While the log likelihood of Model 2 (-37.35) is marginally higher than that of Model 1 (-37.50), the coefficient of vehicle density (-0.024) is not statistically significant. This suggests that the incorporation of vehicle density as a proxy for congestion does not help to predict policy adoption (which is perhaps unsurprising given the high correlation between these two variables, see Table A1 in the Appendix). This modelling result might suggest that Chinese municipalities adopt car restriction policies to respond directly to car ownership rather than the congestion effect caused by high car use and limited road resources. Until recent years, no index of congestion was systematically collected and reported in most Chinese municipalities; however, car ownership has been officially registered and readily accessible to all municipalities looking to make policy decisions based on explicit data.

Model specifications 3 and 4 suggest that the results of Model 1 are largely robust to missing data. Model 3 incorporates interactions between the missing dummy and all other variables in the model, while Model 4 uses only the cities with complete observations for modelling. The only new finding in Models 3 and 4 is that the total urban population is marginally significant, suggesting a positive impact of city size on policy adoption. Overall we find that the key coefficients across the four models are quite stable, particularly those of motor vehicles per capita and API values.

5.2. Elasticity Analysis

While the duration models above help to determine the statistical significance of variables in predicting car restriction policy adoption, because the independent variables are measured on different scales their raw coefficients are difficult to interpret in terms of relative importance. Therefore, here we compute the elasticity of policy adoption probabilities with respect to each variable and compare the magnitudes of their relative impacts.

Figure 1 shows the elasticity of policy adoption probabilities with respect to the variables in Model 1, with black dots representing the values of elasticities and red bars representing the 95% confidence intervals. The confidence intervals of mean API, motor per capita, and maximum API do not intersect zero, echoing the finding that these three variables are statistically different from zero. Furthermore, we find that the most significant variables in Model 1 are also the most substantively predictive of policy adoption; the mean API, motor per capita, and maximum API exhibit the largest elasticities of policy adoption probability. Despite their statistical significance in Model 1, the elasticities of the subway dummy and subway length per capita variables are close to zero, suggesting that the impact of subways is not as large as the elasticities of API and auto ownership per capita. The elasticities of other variables were not significantly different from zero.

With this ranking of covariates by magnitude of impact on the probability of policy adoption, we deepen the argument in the previous section. We conclude that car restriction policies are adopted primarily in response to API values and secondarily to auto ownership. In particular, we find that a 1% increase in a city's yearly mean API value leads to a 1.12% higher likelihood of adopting a car restriction policy. Similarly, a 1% increase in the number of automobiles per capita leads to a 0.93% increase of policy adoption probabilities, and a 1% increase in a city's yearly maximum API value leads to a 0.7% increase in the probability of policy adoption.

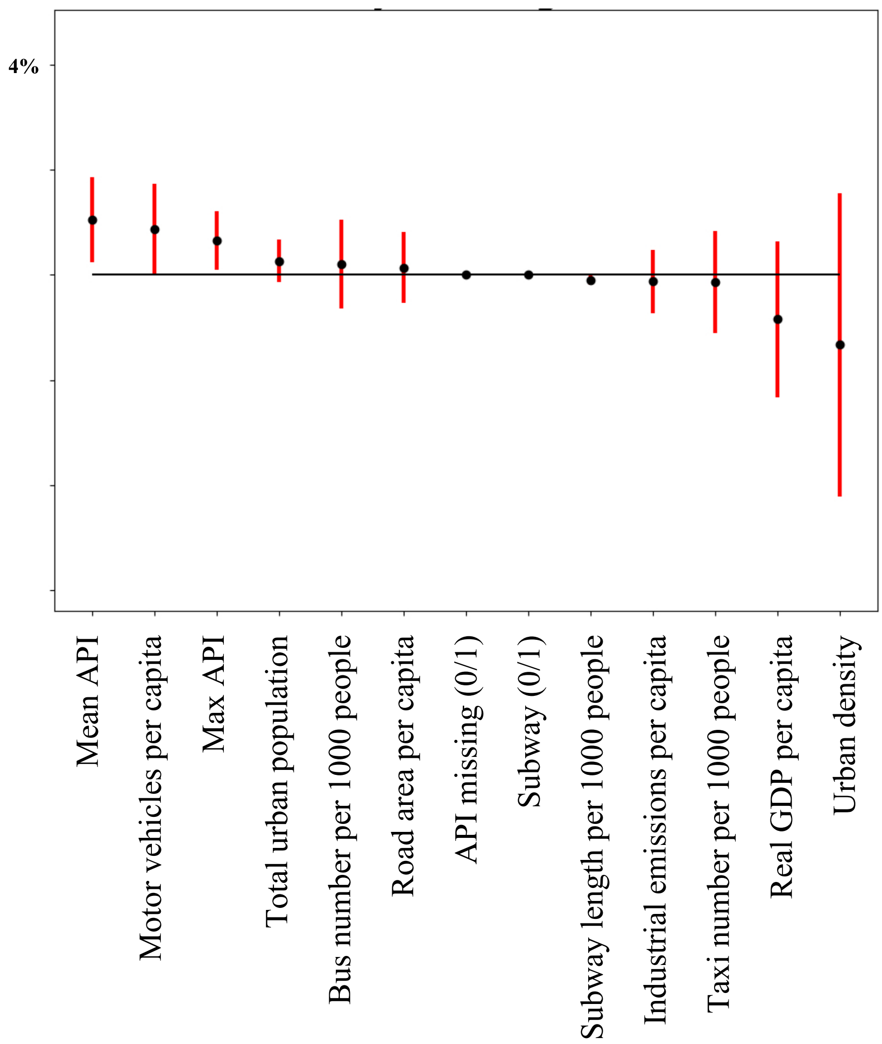


Figure 1. Elasticities of policy adoption probabilities with respect to key variables.

5.3. Provincial and City Effects

As a final robustness test, we run two additional models that add idiosyncratic provincial, P, and city, C, effects to Model 1 (see Table 4). Model 1P explores whether regional effects (such as following provincial mandate or the example of the provincial capital) cause policy adoption in addition to local concerns (hypothesis 4). Model 1C explores if idiosyncratic city effects (such as local culture) that are not captured in our set of city-year covariates cause policy adoption. Both idiosyncratic effects were modeled under the assumption of Gaussian probability distributions, similar to an econometric random effect model.

Comparing across the three models in Table 4, we find that their coefficients are similar in magnitude, implying that our previous findings are robust to provincial and city effects. Additionally, we find that the lower bound of the 95% confidence interval of the coefficients of motor vehicles per capita, mean API mean, and maximum API are all larger than zero, suggesting that the previous statistical significance of these variables also hold true after controlling for the provincial and city effects. The coefficient of subway length becomes insignificant after controlling for provincial and city effects; thus, geographical effects explain away the subway length effect previously identified.

Table 4. Robustness of duration models to provincial and city heterogeneity

	Model 1: Baseline	Model 1P: with Province heterogeneity			Model 1C: with City heterogeneity		
			95% CI Bounds		b	95% CI Bounds	
	b	b	Lower	Upper		Lower	Upper
Motor vehicles per capita	16.46	21.75	2.60	40.89	18.81	0.04	37.57
Mean API	0.04	0.04	0.01	0.08	0.04	0.01	0.078
Max API	0.01	0.01	0.00	0.02	0.01	0.00	0.017
API dummy (0/1)	4.84	5.31	0.25	10.38	4.50	0.05	8.96
Industrial emission per capita	-6.28	-4.13	-31.34	23.08	-3.00	-33.29	27.31
Total urban population	0.19	0.11	-0.28	0.50	0.18	-0.18	0.55
Real GDP per capita	-0.02	-0.03	-0.08	0.02	-0.03	-0.07	0.02
Taxi per capita	-0.17	-0.21	-1.68	1.27	-0.37	-1.79	1.06
Bus per capita	0.81	1.25	-2.68	5.17	1.44	-2.37	5.25
Subway length per capita	-0.33	-0.34	-0.72	0.04	-0.32	-0.71	0.06
Subway dummy (0/1)	3.11	3.54	0.69	6.39	2.99	0.21	5.77
Road area per capita	0.04	-0.02	-0.28	0.25	0.00	-0.24	0.24
Urban density	-0.08	-0.06	-0.24	0.13	-0.06	-0.25	0.13
Log-likelihood	-37.49			-29.89			-25.23
AIC	100.99			61.43			52.09
BIC	106.17			61.76			52.42

Note: b = estimated unstandardized coefficient; CI = confidence interval. Whether the lower and upper bounds of the 95% confidence interval contain zero indicates a variable's statistical significance at the 5% level.

The comparison of Models 1, 1P, and 1C in terms of their model fit—log likelihood, AIC, and BIC—suggest that Models 1P and 1C are preferred to Model 1.[6] This suggests that adding heterogeneous provincial or city effects better explains policy adoption than a homogeneous model. However, these provincial and city effects are difficult to interpret. A single coefficient does not give us insight into the underlying mechanism by which these regional effects influence policy adoption. Potential explanations include command-control decision-making from province to city, policy learning from municipalities at the same level, and cultural or other similarities caused by geographical closeness. It could be that local municipalities follow the policies of the provincial capitals, and this command-and-control mechanism contributes to the provincial effect. Alternatively or in addition, provincial and city effects could be caused by similarity in institutional structure, social norms, public opinion, or other local cultural influences of the cities within one province or of one city across time

[6] Higher log likelihood values are preferred, while lower AIC and BIC scores are preferred. All measures suggest that models with provincial and city effects are preferred.

periods. Given the difficulty in interpreting these provincial and city effects, in this study we only treat Models 1P and 1C as robustness tests to the findings in Model 1.

6. Discussion

This study explores what factors prompt Chinese municipalities to adopt comprehensive car restriction policies. Using a mixed methods approach that combines the qualitative analysis of policy documents and quantitative duration modelling, we posit and test five potential hypotheses for how car restriction policy adoption is driven: by problem solving, power, local transportation and land use conditions, network effects, or other factors. Taken together, our results suggest that the adoption of comprehensive car restriction policies is explained by a combination of problem solving (in response to local air pollution and congestion) and network effects at the city- and provincial-levels. Among these, problem solving is found to be the primary mechanism of car restriction policy adoption in China (hypothesis 1).

We conclude that the adoption of car restriction policies is primarily motivated by air pollution problems. Both the stated objectives in the policy documents and the results of the quantitative policy adoption models support this conclusion. The fact that these two independent data sources agree demonstrates that the stated objectives of these comprehensive car restriction policies are at least partially aligned with the actual conditions driving their adoption.

The results from the qualitative and quantitative investigations also suggest that municipal car restriction policies are adopted in response to local transportation conditions, although they differ in their emphasis on car ownership vs. congestion caused by car use. While our duration models show that car restriction policies respond to car ownership numbers rather than the congestion effect caused by car use, the policy documents suggest that local municipalities still cite congestion as an important problem. One potential explanation of these contradictory findings is that local governments sincerely target congestion (as stated in their policy documents), but our duration model fails to capture this effect since congestion is highly correlated with car ownership and a valid congestion index is hard to obtain. In such a case, the insignificant coefficient of vehicle density in Table 3 could be due to measurement error and other modelling problems, rather than being reflective of true insignificance in predicting policy adoption.

While intuitively cities with more resources or more population would be more likely to adopt car restriction policies (hypothesis 2, power), duration models show that these effects are not significant after controlling for local conditions (except urban population being marginally significant in Models 3 and 4). The impression that it is the wealth and size of China's megacities that drives them to adopt car restriction policies can be caused by the high correlation between local air emissions and transportation problems and a city's size, GDP, and land use patterns (see Table A1 in the Appendix). When it comes to hypothesis 3 related to local transportation and land use conditions, the adoption of car restriction policies does respond marginally to local subway systems, but not to buses or taxis. The insignificance of these variables in explaining the adoption of car restriction policies suggest that the adoption of these policies is not driven by power or other local transportation and land use conditions.

Finally, we find that heterogeneous regional effects (by province or city) contribute to greater predictive power of the duration model. This is evidence of network effects (hypothesis 4) contributing to policy adoption, but we are unable to interpret the specific mechanisms behind these random effects, which is an important area for future research.

6.1. Implications for Municipal Policymaking in China and Beyond

While this study focuses on car restriction policies at the city-level in China, many of our findings have potential implications for municipal policymaking more generally. This study and others like it can help facilitate future discussions about governance structures surrounding automobile management strategies and other municipal transportation policies.

Discovering which of the many competing drivers influence the adoption of certain policies, we can design our policymaking institutions and processes to more effectively and efficiently support these specific drivers. For example, our results corroborate previous research that suggests that much of China's municipal transportation policies are implemented to solve specific problems. This might suggest systematic and clear gathering and reporting of air pollution and congestion information across cities and polls of public opinion around these issues might encourage additional uptake of car ownership and restriction policies across China's cities. In addition, we found that there are significant network effects—or policy learning—across cities and within regions. Therefore, the creation of communication channels or associations among city governments might help to facilitate this policy learning around car restriction policies. Similar approaches could be employed to better identify designs for institutions and processes that could facilitate policymaking in other contexts and domains.

The findings of this study also contribute to an understanding of the relationship between rules-on-books and rules-in-action in Chinese transportation policymaking. Our mixed methods approach indicates at least partial alignment between the motivations written down in policy documents and the real-world conditions that prompt adoption of car ownership and use restriction policies in China. The objectives cited in the policy documents are consistent with our modelling findings, implying that motivations-on-book and motivations-in-reality aligned with each other. This suggests that municipalities are properly identifying key policy objectives in law and reinforcing these through policy implementation in action. Typically, we expect this alignment in cities with sound legal and legislative systems where governments have the capacity to implement complementary rules-on-books and rules-in-action. Our findings suggest that the municipalities in China have both the capacity to efficiently implement rules-on-books and to absorb feedbacks to make legislative acts. Future policymaking in Chinese (and potentially other) cities could take advantage of this virtuous feedback to implement more effective transportation policies by setting clear policy goals that can guide implementation of effective policies. These results may also suggest that policy documents may be a credible source of information for future analysis of drivers of policy adoption. With the growing popularity and ease of use of natural language processing tools, the text within policy documents, if truly reflecting reality, may open up a new realm of policy research in the future.

6.2. Implications for Policy Adoption Analysis in the Transportation Domain: Limitations and Future Work

In addition to implications for policymaking, our study also makes important methodological contributions by using duration models to analyse the adoption of local transportation policies. Our study highlights the insights that can be gained by treating transportation policy adoption as an endogenous variable (rather than an exogenous one). While duration models (as a natural extension of discrete choice models) are often used in the transportation field for other applications, they have not been widely used for examining transportation policy adoption. Future transportation scholars can use this study as an example of how to apply these models to examine the adoption of transportation policies across different levels of government. As the world continues to define new sustainable transportation policy portfolios, this quantitative understanding of policy adoption may be as critical as policy evaluation for facilitating policy learning across cities and countries.

In applying this method to new applications, researchers and practitioners should be aware of a few remaining caveats. While the duration model used in this study is a state-of-the-practice model that takes into account unobserved heterogeneity across provinces and cities, it assumes a parametric Gaussian distribution (similar to a random effects approach), which may not reflect reality. Without additional sensitivity tests across different distributional assumptions, the findings about provincial and city effects can only be interpreted as a robustness test, and we unfortunately cannot articulate the explicit decision-making mechanisms represented by provincial and city effects. City case studies and more in-depth qualitative and quantitative analysis would be needed to explain these idiosyncratic provincial and city effects in policymaking.

While our duration models improve upon choice models by including a temporal dimension, the temporal dimension in the duration model is simplified to a conditional probability assumption without concerning long-term time effects. While data sparsity may prove a limitation, long-term time effects could be analysed by explicit time series modelling. This modelling effort may also consider additional economic, transportation, and urbanization indicators not investigated in this analysis, such as more appropriate measures of city-level congestion, the presence of other rapid transit infrastructure (such as BRT lines) in addition to subway systems, etc. if appropriate and consistent data sources can be identified.

Finally, a generic weakness of this study is that post-policy adoption duration modelling and analysis of policy documents cannot show how air pollution and transportation conditions are taken into account in the policy formulation and implementation process. While our results suggest that these are important factors, future studies, such as in-depth interviews with municipal government officials, are needed to delve into the details of how these factors are considered within the policy decision-making of local governments.

7. Conclusion

This study adopts a novel mixed methods approach to understand what factors drive a Chinese city to decide whether or not to adopt a comprehensive (i.e., city-wide, year-round, and inclusive of most vehicle types) car ownership or use restriction policy in a given year. We qualitatively investigate the stated purpose and legislative precedent cited in 116 car ownership and use restriction policy documents. Combining the policy information with indicators of socio-economic, urban, and transportation condition, we quantitatively model how local conditions predict the adoption of car restriction policies using a database of 287 cities from 2001 to 2014.

We show that the adoption of car restriction policies among Chinese municipalities respond to local air pollution problems and local transportation conditions (such as motorization and congestion). While these findings may be expected, our quantitative analysis suggests that these justifications are more than lip service; actual air quality and vehicle ownership levels over the past 14 years at least partially explain the adoption of comprehensive car ownership and use restrictions across 287 cities in China. And our quantitative conclusions are robust to various model specifications, missingness in the data, data size, and unobserved heterogeneities across provinces or cities.

While contributing to understanding of transportation policymaking among Chinese municipalities, this study also provides a potential template for other modelling efforts in predicting policy adoption in Chinese cities and beyond. In transportation modelling, researchers often aim to predict fleet size or travel patterns; the results of this study suggest that transportation policy decision may be a critical endogenous part of those predictive models that is often overlooked. In fact, the prediction of car ownership cannot be precise without considering the adoption of car restriction policies. Furthermore, this study shows that duration models can be used to analyse the policy decision-making process. These models are superior to traditional choice models because they explicitly capture average temporal effects. Nonetheless, this study still has some limitations in its modelling, measurement, and interpretability of modelling results that must be addressed with future research. However, we hope this study could pave the way for future mixed-methods analysis into municipal transportation policy decisions as cities around the world continue to experiment with new automobile management and other sustainable transportation policies.

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Appendix

Table A1. Pearson (linear) correlations among independent variables across the 287 Cities from 2001-2014

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Motor vehicles per capita													
2	Mean API	0.319												
3	Max API	0.298	0.85											
4	API dummy (0/1)	-0.339	-0.918	-0.807										
5	Industrial emission per capita	0.231	0.023	0.051	-0.021									
6	Total urban population	0.467	0.313	0.361	-0.322	-0.029								
7	Real GDP per capita	0.874	0.281	0.28	-0.329	0.265	0.483							
8	Taxi per capita	0.54	0.279	0.353	-0.298	0.354	0.469	0.608						
9	Bus per capita	0.716	0.34	0.369	-0.389	0.182	0.573	0.793	0.752					
10	Subway length per capita	0.381	0.17	0.187	-0.174	-0.039	0.647	0.363	0.318	0.422				
11	Subway dummy (0/1)	0.427	0.212	0.226	-0.211	-0.031	0.703	0.44	0.398	0.52	0.775			
12	Road area per capita	**0.744**	0.239	0.239	-0.294	0.337	0.432	0.833	0.675	0.73	0.261	0.349		
13	Urban density	-0.033	-0.169	-0.159	0.179	-0.079	0.151	-0.038	-0.106	-0.069	-0.015	-0.02	0.079	